UniversalBank_Naive Bayes

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```
library(ggplot2)
library(lattice)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(readr)
library(caret)
library(dplyr)
library(knitr)
library(e1071)
library(class)
library(ISLR)
```

#Importing Data set

```
#importing Data set and converting
getwd()

## [1] "/Users/avinashravipudi/Desktop/FMLAssignment3"

UB<-read.csv("UniversalBank.csv")
#summarize the Data
str(UB)

## 'data.frame':    5000 obs. of  14 variables:
##  $ ID                : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Age               : int  25 45 39 35 35 37 53 50 35 34 ...
##  $ Experience        : int  1 19 15 9 8 13 27 24 10 9 ...
##  $ Income            : int  49 34 11 100 45 29 72 22 81 180 ...
##  $ ZIP.Code          : int  91107 90089 94720 94112 91330 92121 91711
93943 90089 93023 ...
##  $ Family            : int  4 3 1 1 4 4 2 1 3 1 ...
##  $ CCAvg             : num  1.6 1.5 1 2.7 1 0.4 1.5 0.3 0.6 8.9 ...
##  $ Education         : int  1 1 1 2 2 2 2 3 2 3 ...
```

```
##  $ Mortgage         : int  0 0 0 0 0 155 0 0 104 0 ...
##  $ Personal.Loan     : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ Securities.Account: int  1 1 0 0 0 0 0 0 0 0 ...
##  $ CD.Account        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Online            : int  0 0 0 0 0 1 1 0 1 0 ...
##  $ CreditCard        : int  0 0 0 0 1 0 0 1 0 0 ...
```

```
head(UB)
```

```
##   ID Age Experience Income ZIP.Code Family CCAvg Education Mortgage
## 1  1  25          1     49    91107      4   1.6         1        0
## 2  2  45         19     34    90089      3   1.5         1        0
## 3  3  39         15     11    94720      1   1.0         1        0
## 4  4  35          9    100    94112      1   2.7         2        0
## 5  5  35          8     45    91330      4   1.0         2        0
## 6  6  37         13     29    92121      4   0.4         2      155
##   Personal.Loan Securities.Account CD.Account Online CreditCard
## 1             0                  1          0      0          0
## 2             0                  1          0      0          0
## 3             0                  0          0      0          0
## 4             0                  0          0      0          0
## 5             0                  0          0      0          1
## 6             0                  0          0      1          0
```

#Checking for Missing Values

```
colMeans(is.na(UB))
```

```
##                 ID                Age         Experience
Income
##                  0                  0                  0
0
##           ZIP.Code             Family              CCAvg
Education
##                  0                  0                  0
0
##           Mortgage      Personal.Loan Securities.Account
CD.Account
##                  0                  0                  0
0
##             Online         CreditCard
##                  0                  0
```

#Converting & Summary online variables

```
DF_UB<-UB%>%
select(Age,Experience,Income,Family,CCAvg,Education,Mortgage,Personal.Loan,Se
curities.Account,CD.Account,Online,CreditCard)

DF_UB$CreditCard <- as.factor(DF_UB$CreditCard)
summary(DF_UB$CreditCard)
```

```
##    0    1 
## 3530 1470

is.factor(DF_UB$CreditCard)

## [1] TRUE

DF_UB$Personal.Loan <- as.factor((DF_UB$Personal.Loan))
summary(DF_UB$Personal.Loan)

##    0    1 
## 4520  480

is.factor(DF_UB$Personal.Loan)

## [1] TRUE

DF_UB$Online <- as.factor(DF_UB$Online)
summary(DF_UB$Online)

##    0    1 
## 2016 2984

is.factor(DF_UB$Online)

## [1] TRUE
```

#split data 60% Training and 40% validation

```
selected.var <- c(8,11,12)
set.seed(1)
Train_Index = createDataPartition(DF_UB$Personal.Loan, p=0.60, list=FALSE)
Train_Data = DF_UB[Train_Index,selected.var]
Validation_Data = DF_UB[-Train_Index,selected.var]
```

#A.Pivot Table for credit card, Loan & Online

```
attach(Train_Data)
ftable(CreditCard,Personal.Loan,Online)

##                          Online    0    1
## CreditCard Personal.Loan                 
## 0          0                     780 1126
##            1                      77  120
## 1          0                     303  503
##            1                      39   52

detach(Train_Data)
```

The pivot table is now created with online as a column, Credit Card and LOAN as rows.

#B) (probability not using Naive Bayes) With Online=1 and Credit Card=1, we can calculate the likelihood that Loan=1 by , we add 52(Loan=1 from ftable) and 503(Loan=0 from ftable) which gives us 555. Probability= 52/555 = 0.09369 or 9.36% . Hence the probability is 9.36%

```
prop.table(ftable(Train_Data$CreditCard,Train_Data$Online,Train_Data$Personal
.Loan),margin=1)

##               0          1
##
## 0 0  0.91015169 0.08984831
##   1  0.90369181 0.09630819
## 1 0  0.88596491 0.11403509
##   1  0.90630631 0.09369369
```

The above table shows chances of geting a loan if you have a credit card and you apply online

#C: pivot table between personal loan and online , personal loan & credit card

```
attach(Train_Data)
ftable(Personal.Loan,Online)

##               Online    0    1
## Personal.Loan
## 0                    1083 1629
## 1                     116  172

ftable(Personal.Loan,CreditCard)

##               CreditCard    0    1
## Personal.Loan
## 0                        1906  806
## 1                         197   91

detach(Train_Data)
```

The two pivot tables of above written as follows 1.In First pivot table: Online as a column & personal loan as row 2.In second Pivot table: Credit card as column & personal row as row

#D Propotion Pivot table

```
prop.table(ftable(Train_Data$Personal.Loan,Train_Data$CreditCard),margin=1)

##            0         1
##
## 0  0.7028024 0.2971976
## 1  0.6840278 0.3159722

prop.table(ftable(Train_Data$Personal.Loan,Train_Data$Online),margin=1)

##            0         1
##
## 0  0.3993363 0.6006637
## 1  0.4027778 0.5972222
```

The code above displays a proportion pivot table that can assist in answering question D.
D1) 91/288 = 0.3159 or 31.59%
D2) 172/288 = 0.5972 or 59.72% D3) total loans= 1 from table (288) is now divided by total count from table (3000) = 0.096 or 9.6% D4) 806/2712 = 0.2971 or 29.71% D5) 1629/2712 = 0.6006 or 60.06% D6) total loans=0 from table(2712) which is divided by total count from table (3000) = 0.904 or 90.4%

#E)Naive Bayes calculation (0.3159 * 0.5972 * 0.096)/[(0.3159 * 0.5972 * 0.096)+(0.2971 * 0.6006 * 0.904)] = 0.0528913646 or 5.29%

#F) While E uses probability for each of the counts, B does a direct computation based on a count. As a result, B is more exact, but E is best for broad generality.

##G)

```
Universal.nb <- naiveBayes(Personal.Loan ~ ., data = Train_Data)
Universal.nb

##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##     0     1
## 0.904 0.096
##
## Conditional probabilities:
##    Online
## Y           0         1
##   0 0.3993363 0.6006637
##   1 0.4027778 0.5972222
##
##    CreditCard
## Y           0         1
##   0 0.7028024 0.2971976
##   1 0.6840278 0.3159722
```

While understanding how you're computing P(LOAN=1|CC=1,Online=1) using the Naive Bayes model is made straightforward by utilizing the two tables created in step C, you can also rapidly compute P(LOAN=1|CC=1,Online=1) using the pivot table created in step B.

Although it is less than that determined manually in step E, the probability predicted by the Naive Bayes model is the same as that projected by the prior techniques. This probability is closer to the one discovered in step B. This might be the case since step E's calculations are done manually, which leaves space for mistake when rounding fractions and results in approximations.

#NB confusion matrix for Train_Data

```
pred.class <- predict(Universal.nb, newdata = Train_Data)
confusionMatrix(pred.class, Train_Data$Personal.Loan)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2712  288
##          1    0    0
##
##                Accuracy : 0.904
##                  95% CI : (0.8929, 0.9143)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : 0.5157
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 1.000
##             Specificity : 0.000
##          Pos Pred Value : 0.904
##          Neg Pred Value :   NaN
##              Prevalence : 0.904
##          Detection Rate : 0.904
##    Detection Prevalence : 1.000
##       Balanced Accuracy : 0.500
##
##        'Positive' Class : 0
##
```

Despite being extremely sensitive, this model showed a low specificity. Although the reference had all actual values, the model predicted that all values would be zero. Due to the high amount of 0 values, the model still provides a 90.4 percent accuracy even when all 1 data were absent.

##Validation set

```
pred.prob <- predict(Universal.nb, newdata=Validation_Data, type="raw")
pred.class <- predict(Universal.nb, newdata = Validation_Data)
confusionMatrix(pred.class, Validation_Data$Personal.Loan)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1808  192
##          1    0    0
##
```

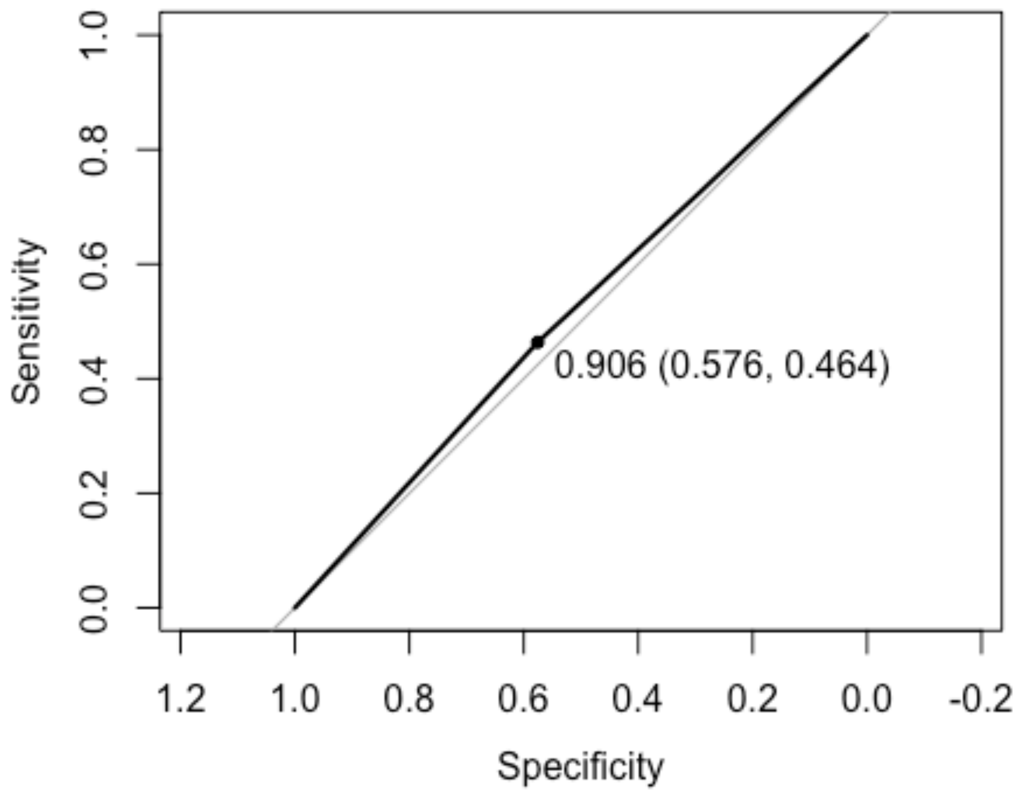
```
##                Accuracy : 0.904
##                  95% CI : (0.8902, 0.9166)
##     No Information Rate : 0.904
##     P-Value [Acc > NIR] : 0.5192
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 1.000
##             Specificity : 0.000
##          Pos Pred Value : 0.904
##          Neg Pred Value :   NaN
##              Prevalence : 0.904
##          Detection Rate : 0.904
##    Detection Prevalence : 1.000
##       Balanced Accuracy : 0.500
##
##        'Positive' Class : 0
##
```

Let’s take a visual look at the model to determine what the optimal threshold is for it.

#ROC

```
library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

roc(Validation_Data$Personal.Loan,pred.prob[,1])

## Setting levels: control = 0, case = 1

## Setting direction: controls < cases

##
## Call:
## roc.default(response = Validation_Data$Personal.Loan, predictor = 
pred.prob[,     1])
##
## Data: pred.prob[, 1] in 1808 controls (Validation_Data$Personal.Loan 0) < 
192 cases (Validation_Data$Personal.Loan 1).
## Area under the curve: 0.5193

plot.roc(Validation_Data$Personal.Loan,pred.prob[,1],print.thres="best")
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```



Setting a threshold of 0.906 improves the model by decreasing sensitivity to 0.464 and improving specificity to 0.576. ```